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Exploring the utility of Bayesian Networks for modelling cultural ecosystem services: A canoeing case study

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HIGHLIGHTS

- We assessed how suitable Bayesian Networks are for modelling cultural services.
- Our BN successfully captured the subjective opinions of our stakeholders.
- Discrepancies arose due to the laborious process of eliciting stakeholder input.
- These were also caused by uncertainty propagation down longer chains of variables.
- These problems can be avoided by representing cultural service as simple network.

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ABSTRACT

Modelling cultural ecosystem services is challenging as they often involve subjective and intangible concepts. As a consequence they have been neglected in ecosystem service studies, something that needs remedying if environmental decision making is to be truly holistic. We suggest Bayesian Networks (BNs) have a number of qualities that may make them well-suited for dealing with cultural services. For example, they define relationships between variables probabilistically, enabling conceptual and physical variables to be linked, and therefore the numerical representation of stakeholder opinions. We assess whether BNs are a good method for modelling cultural services by building one collaboratively with canoeists to predict how the subjective concepts of fun and danger are impacted on by weir modification.

The BN successfully captured the relationships between the variables, with model output being broadly consistent with verbal descriptions by the canoeists. There were however a number of discrepancies indicating imperfect knowledge capture. This is likely due to the structure of the network and the abstract and laborious nature of the probability elicitation stage. New techniques should be developed to increase the intuitiveness and efficiency of probability elicitation. The limitations we identified with BNs are avoided if their structure can be kept simple, and it is in such circumstances that BNs can offer a good method for modelling cultural ecosystem services.

1. Introduction

Predicting how the supply of ecosystem service (ES) will respond to ecosystem change is fundamental to the implementation of the ES framework. Yet despite a substantial and growing body of research on the subject, a number of research challenges remain (Millennium Ecosystem Assessment (MA), 2005; Daily et al., 2009; Fisher et al., 2009; de Groot et al., 2010). One of these is how the supply of cultural services can be predicted, an important class of service commonly neglected in ES studies (Raudsepp-Hearne et al., 2010; Schaich et al., 2010; Daniel et al., 2012; Milcu et al., 2013).

Cultural services include nonutilitarian and nonconsumptive benefits provided by ecosystems, such as sources of creative inspiration, or aesthetic, existence or recreational values (MA, 2005; Daniel et al., 2012; Milcu et al., 2013). They have a number of qualities that makes their integration into ES modelling difficult (Norton et al., 2012). Many are intangible, are experienced in an intuitive and subjective fashion, and involve nebulous concepts such as 'naturalness', 'identity' and 'excitement' (Chan et al., 2012; Milcu et al., 2013). Their supply is generated through a complex interaction between ecosystems and people (Church et al., 2014). The capture of perceptions and values in models is considered a key research direction in the development of tools to aid environmental decision making (Borowski and Hare, 2007).

A powerful modelling approach with properties suited to dealing with cultural services is the Bayesian Network (BN). The structure of a

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BN is formed by a directed acyclic graph (DAG), where variables and the cause–effect relationships between them are represented by nodes and edges (Jensen and Nielsen, 2007). Each variable is defined as a set of discrete states or series of ranges, and the conditional relationships between them are described probabilistically (Jensen and Nielsen, 2007). Not only have they been used to build decision support tools in a wide variety of contexts such as medical diagnosis (Kahn et al., 1997), image processing (Yang et al., 2002), urban planning (Kumar et al., 2013), land classification (Passuello et al., 2014), and catchment management (Holzkämper et al., 2012), their potential for modelling ecosystem services has also been recognised (Haines-Young, 2011; Landuyt et al., 2013; Church et al., 2014).

BNs have a number of qualities that appear to equip them for handling the challenges presented by cultural ESs. The aim of many decision support tools is to combine, interpret and communicate knowledge from diverse scientific disciplines to decision makers in such a way that an entire cause–effect chain can be evaluated from a synoptic perspective, something BNs do well (Kumar et al., 2013). By describing relationships between variables probabilistically, BNs can integrate relationships derived from data, other models, and the judgement of individuals (Haines-Young, 2011; Holzkämper et al., 2012; Landuyt et al., 2013). This includes relationships involving the perceptions and judgements of value typical of cultural ecosystem services. Probabilities can also capture differences in opinion between stakeholders which are represented as uncertainty within the model (Holzkämper et al., 2012); important when dealing with the inherently variable nature of subjective variables. Furthermore, they allow relationships between variables to be defined even when the mechanism connecting them is unknown (Daly et al., 2011).

Because BNs are structured as graphical cause–effect networks, model construction is considered more intuitive and transparent than other modelling approaches, facilitating stakeholder participation and consensus building during model development (Borsuk et al., 2004; Haines-Young, 2011; Landuyt et al., 2013). Even the need to discretise variables, a weakness when modelling the continuous gradients common in the physical world (Landuyt et al., 2013), is less of an issue in the context of cultural services modelling. This is because discretisation is consistent with human perception, as our mental models of the world are based on its categorisation (e.g. red/orange/yellow, tall/medium/small) (Harnad, 2005). These attributes allow BNs to serve as a tool that through a logical process can consolidate the views of multiple experts and make evidence explicit, thereby enabling a more considered approach to decision making.

While BNs appear on paper to be well-suited to dealing with cultural ecosystem services, we are unaware of any attempted applications. In this paper we assess whether BNs are a good method for modelling cultural ecosystem services. We do this by building a BN collaboratively with canoeists to model the fun and danger of the River Don, UK, which is impacted on by the management issue of weir modification.

2. Methods

2.1. Case study description

The River Don is located in northern England and serves as the case study location (Fig. 1). Canoeing is a popular and growing recreational activity in the UK, with 1.78 million people estimated to have participated in paddlesports in 2010 (North, 2011). Multiple canoe groups use the River Don for their sport.

Of significance to canoeists are the many weirs (low-head run-of-the-river dams) that impound the catchment. These structures were built mainly for water power and navigation purposes, and are typically 1–3 m tall, with the steepness of the downstream face ranging from vertical to shallow. The weirs have a big impact on river ecology, primarily by inhibiting riverine connectivity, and for that reason there is considerable interest in their modification (Shaw, 2012).

Canoeists chute (canoe over and descend) various weirs as they paddle stretches of the River Don, and indeed one stretch is known as the Five Weirs Paddle. Weirs affect the recreational value of the River Don both positively and negatively. The excitement of chuting weirs can be a fun experience. However weirs can also be very dangerous, posing a drowning risk. Fun and danger are both dependent on the physical attributes of a weir, and are altered when a weir is modified (e.g. weir height is changed).

2.2. Construction of the canoeing BN

2.2.1. Identification of model structure

An overview of the process of constructing the canoeing BN is presented in Fig. 2. The first step was the identification of the BN structure i.e. the directed acyclic graph (DAG), and involved the identification of the physical and conceptual variables that determine the impact of weirs on river quality for canoeing. These variables are depicted as nodes within the BN, and the causal relationships that link them as edges. The independent and dependent variables in a pair of linked nodes are termed 'parent' and 'child' nodes.

BN structure was built deliberatively over two workshops attended by five canoeists which collectively represented three local canoeing groups. As the canoeists were interested in the conceptual variables of weir danger and weir fun, these were designated as the basal child nodes (Fig. 3a) (i.e. the variables we want to predict). To these the determining physical variables were added. It emerged, for instance, that danger is determined by two factors: 'drawback' i.e. the hydraulic roller at the foot of a weir that pulls the canoeist back towards the weir into cascading water, and the risk of obtaining injury from an impact with the fabric of the weir structure or river bed (see Fig. 3b). The delineation of the DAG was completed when weir modification option nodes i.e. the management variables (changing weir height, steepness, orientation, profile of weir face, and installation of a canoe pass) were incorporated and agreed unimportant nodes were discarded.

2.2.2. Discretisation of variables

The discretisation of the variables also occurred at the workshops. When variables were subjective (e.g. weir fun), states were defined collaboratively as descriptive categories (e.g. weir fun is high when it is exciting or enjoyable to descend). For the physical variables (e.g. weir steepness) we made use of predefined categories (e.g. see Fig. 4). The objective of the discretisation was to produce a common definition of the variable states, and to set thresholds between states that when crossed tells us something about the likely state of the dependent variable (Kumar et al., 2008). For instance, weir danger initially increases rapidly with weir height, but the rate of increase diminishes until a maximum danger is reached (i.e. certain death). Setting a weir height threshold at 1 m is more useful than at 10 m, as the canoeists are able to tell us with confidence that weirs smaller than 1 m will likely pose less of a danger than taller weirs. In contrast not much can be said about the danger posed by weirs smaller than 10 m, as it ranges from negligible to close to the maximum possible.

2.2.3. Probability elicitation

Probability elicitation requires the expert to estimate the probability that each of the child node states (i.e. the dependent variable states) will occur given the states of the parent nodes (the states of the independent variables). As the number of combinations of parent node states grows exponentially with model complexity (Kumar et al., 2008), it quickly becomes impractical for probabilities for larger models to be directly elicited. The sub-network of weir fun for example (see Fig. 3c), with seven parent nodes, needs probabilities for each of the 2916 combinations of parent node states. For this reason we employed a modified version of the relative weight and compatible probability method proposed by Das (1999). This allowed us to reduce the number of questions to 120, from which the remaining conditional probabilities could be

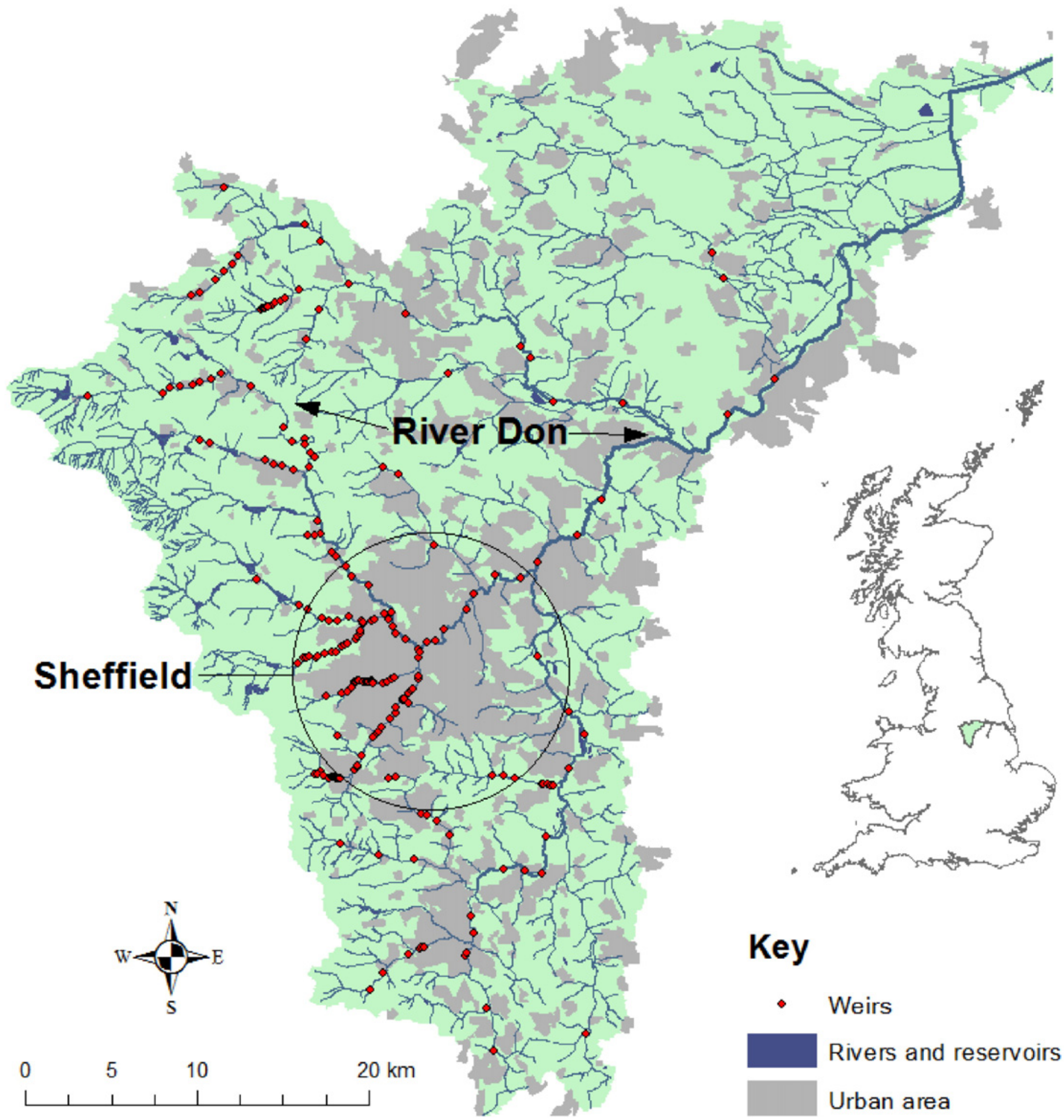

Fig. 1. Map of the Don Catchment showing the River Don, the city of Sheffield, and the distribution of weirs.

interpolated (Das, 1999). The questionnaire was designed to allow for the nonlinearity we knew from the workshops to exist between some variables e.g. weirs of an intermediate steepness have a greater degree of drawback than steeper or shallower weirs. This was achieved by eliciting probabilities for a range of parent node states that included those that maximise and minimise the child node state probabilities, thereby producing threshold responses. The questionnaire also obtained for each subnetwork weightings of the relative strength of the parent nodes (from 1–10) in influencing the child node.

An example question is presented in Fig. 5. The question elicits a set of probabilities for the weir fun subnetwork (see Fig. 3c), and requires that the canoeists estimate how likely weir fun (the dependent variable) will be high, medium and low given the states of the determining variables. Since not all experts are familiar with probabilities and are more comfortable expressing their beliefs with words, the questions included a scale with both verbal and numerical intervals. As the weir fun subnetwork is the largest in the model, this was the most complex question put to the canoeist as they must simultaneously consider the effect of the seven independent variables. To ease the process we prepared supporting materials with illustrative figures e.g. Fig. 4b.

The questionnaires were posted to the workshop participants. However, as none were returned, it was necessary to recruit three

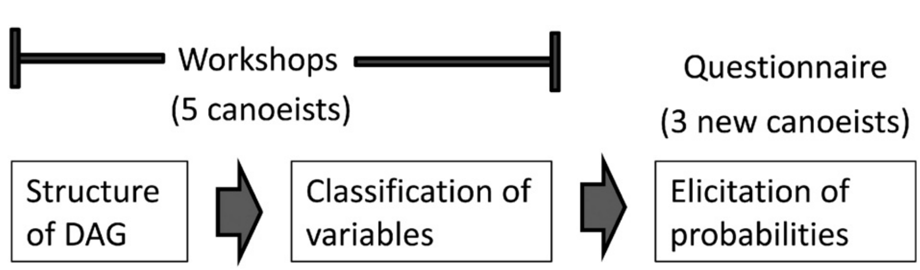

Fig. 2. Overview of the process of the construction of the canoeing BN.

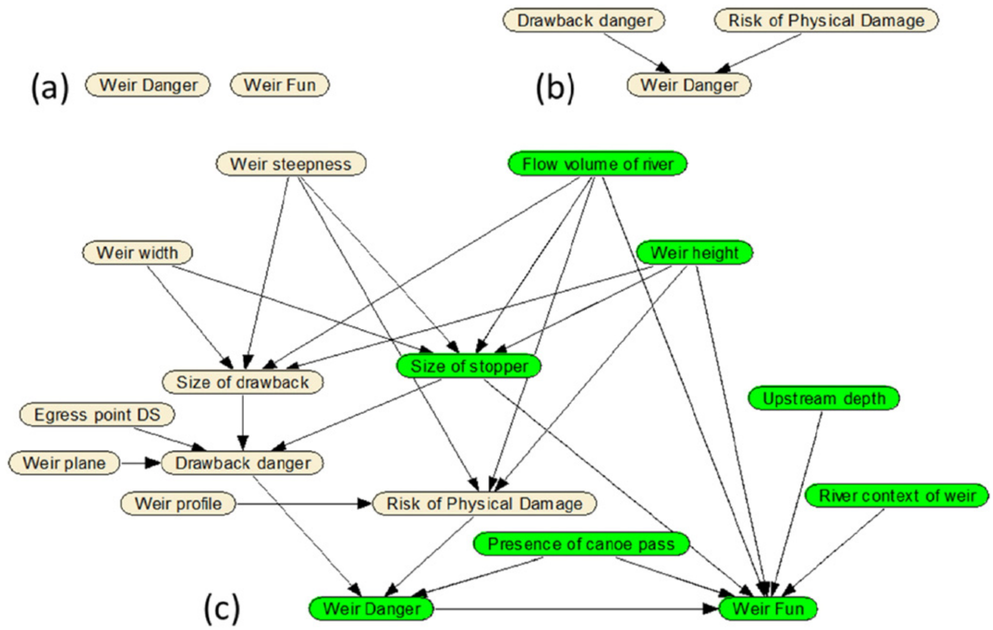

Fig. 3. The evolution of the BN structure in the identification of model variables and structure stage. a) The subjective variables of weir danger and fun which served as the basal nodes, b) weir danger was found to be controlled by the weir drawback and risk of physical injury descending the weir, c) the final canoeing BN structure with all remaining parent nodes and linkages identified. The subnetwork determining weir fun is coloured green.

new canoeists whom we personally supervised to fill out the questionnaires in face-to-face interviews. While the number of experts was low, this is often the case with BNs as it is difficult to find many domain experts willing to commit the time required for model construction (Richardson and Domingos, 2003). In such circumstances it is often better to focus on obtaining comprehensive and thorough ('deeper') knowledge from available high quality experts, which is why we chose experts with >8 years of canoeing experience. This contrasts with the 'broader' knowledge that arises from spending less time with individual experts so that a greater number can be interrogated.

The elicited probabilities were first checked for inconsistencies, and then the conditional probability tables were compiled by interpolating the questionnaire responses. The median values of the combined probabilities were used to train the BN using the commercially available BN modelling software Netica (V4.18).

3. Results

The output of the canoeing BN is demonstrated with two hypothetical scenarios set to maximise and minimise danger to canoeists, both with and without canoe passes (see Fig. 6). The presence or absence of a canoe pass is the most important variable determining weir danger, suggesting that canoeists perceive canoe passes as being highly effective at reducing weir danger. Weir fun on the other hand is most sensitive to river flow, with the probability that fun will be high increasing by as much as 29% when flow is high as opposed to low.

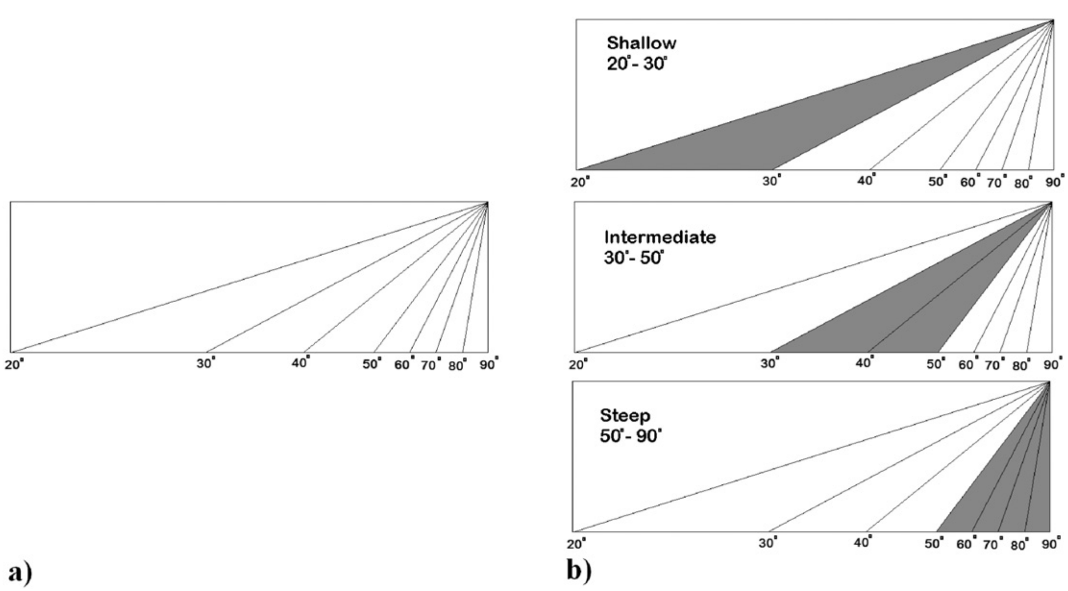

Fig. 4. a) Visual aid used to help the canoeists classify the states for the variable weir steepness. b) The resulting ranges of weir steepness allocated to the discrete states of shallow, intermediate and steep.

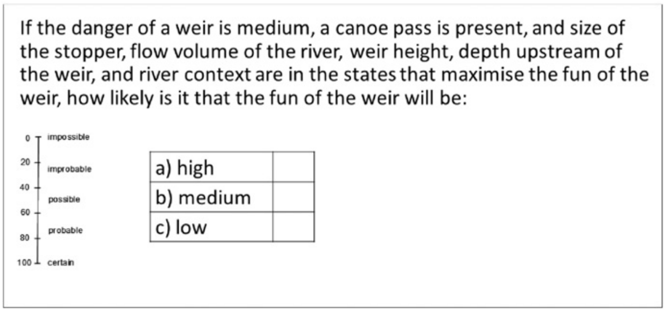

Fig. 5. An example probability elicitation question.

Table 1
The effect of weir changes on weir danger and fun. The effect of each modification was tested while the other predictive variables were balanced across all of their potential states (e.g. 33% high, 33% medium, 33% low).

Change to weir	Weir danger	Weir fun
Canoe pass installation	+ve (less dangerous)	+ve
Increasing weir profile roughness	−ve	NA[1]
Increasing weir height	−ve	+ve
Increasing weir steepness	−ve	Trivial[2]
Change weir plane to ‘smiling’	+ve	NA
Change weir plane to orthogonal	−ve	NA
Increase flow of river	+ve	+ve

[1] Not applicable as node not connected to weir fun.
[2] <1% change.

In Table 1, the effects of the management variables on weir fun and danger are presented. All of the options affect weir danger, though only canoe pass installation has a big effect. Weir fun is only affected by canoe pass installation, weir height, and river flow. The model also finds weir fun and weir danger to be correlated, though this is not surprising since danger influences excitement.

Some of the management variables only have a small effect on the BN output. The main example is weir orientation, with weir danger changing <5% between the ‘smiling’, orthogonal, and ‘frowning’ states (see Fig. 7).

4. Discussion

4.1. Knowledge capture

The capture of the canoeist's perceptions was generally successful, with the predictions of the canoeing BN by and large corresponding with the verbal descriptions of the canoeists. However, there were multiple small inconsistencies that demonstrate some of the limitations with BNs. A number of the model variables were described as strongly

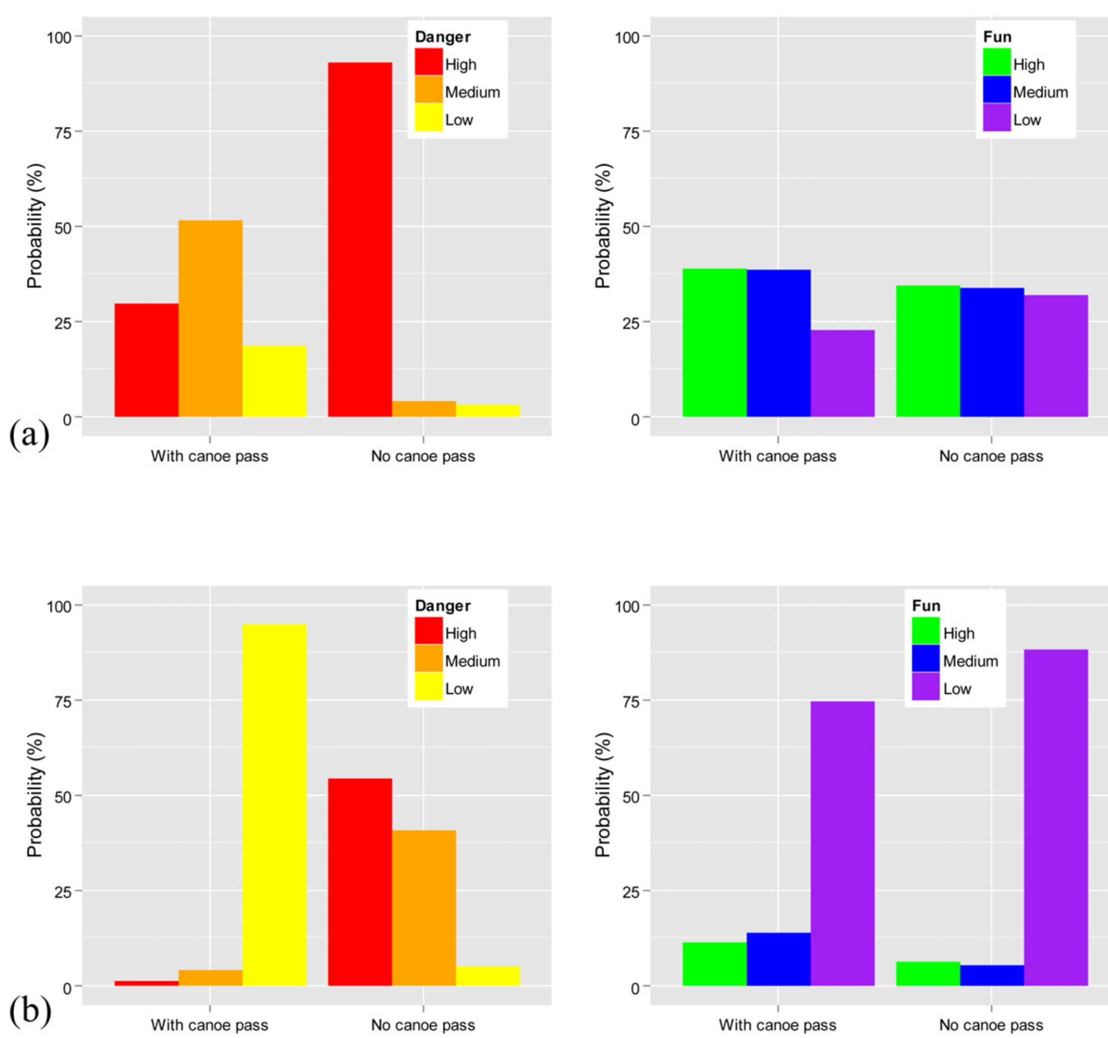

Fig. 6. The output of the canoeing BN for two scenarios with and without canoe passes installed. (a) The river is upland, rapid and has a high flow. The weir is high, narrow, has a rough profile, of an intermediate steepness and a perpendicular plane. (b) The river is lowland, slow and has a low flow. The weir is low, wide, has a smooth profile, of a low steepness and a ‘smiling’ plane.

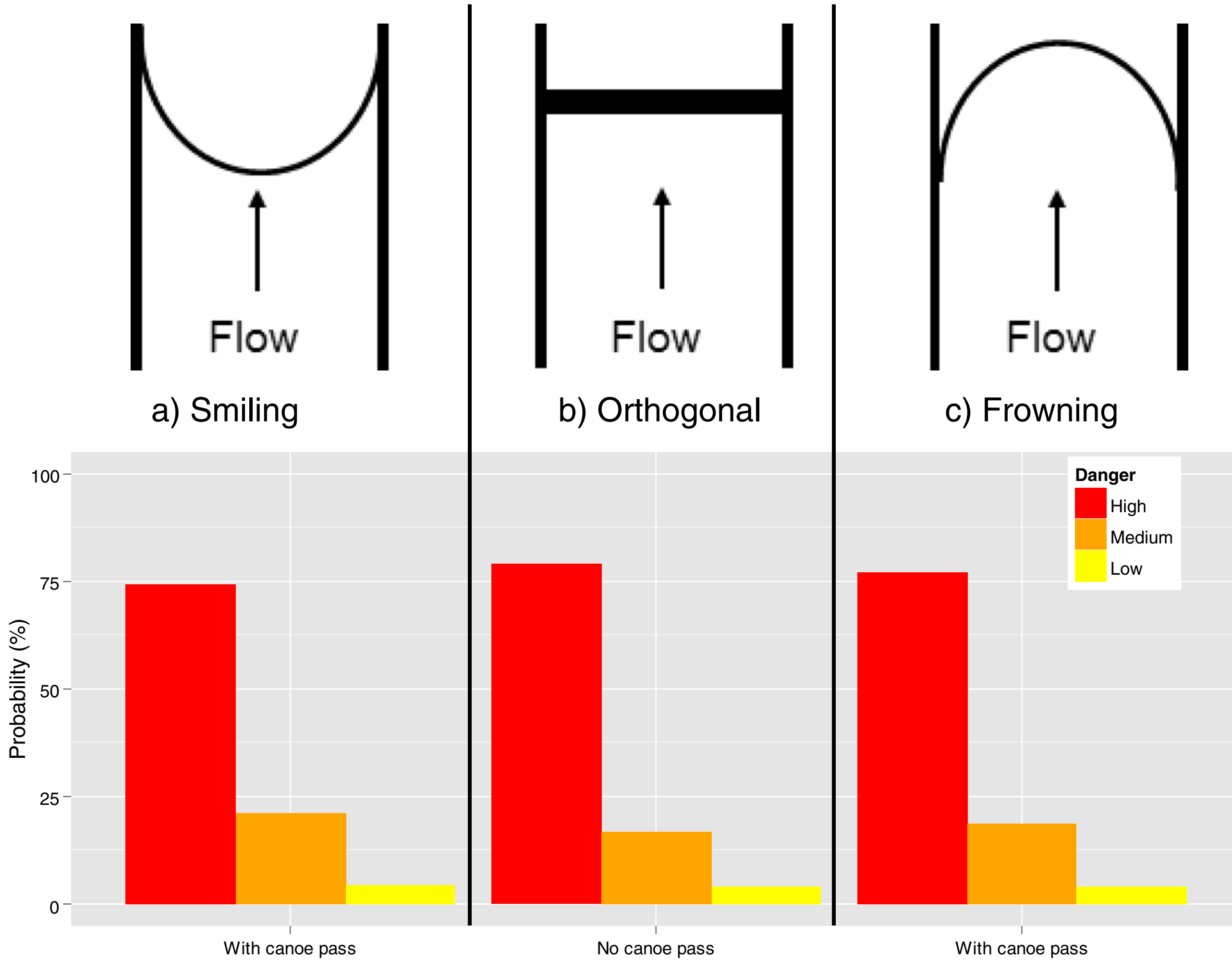

Fig. 7. Weir danger BN predictions for three weir orientations described by the canoeists as being least dangerous (a), of an intermediate danger (b) and most dangerous (c).

determining weir danger, while in the BN only the presence or absence of a canoe pass has a major effect. This is particularly exemplified by weir orientation, with which there was strong consensus amongst the canoeists that the most dangerous orientation was one that was 'frowning' (from the perspective of the canoeist facing downstream (see Fig. 7)), as these are difficult to escape. In contrast, 'smiling' weirs, with the opposite shape, were considered much safer. That the BN predicts little difference between the dangers posed by these orientations demonstrates imperfect knowledge capture during the probability elicitation stage.

The model discrepancies were caused by two main factors. The low importance of the other weir modification options relative to the canoe pass is due to their position in the DAG. The canoe pass node is connected directly to the weir danger node, whereas the other nodes such as weir steepness and orientation are connected through several intermediate nodes, forming longer chains of variables. The high uncertainties at the intermediate nodes weakens the inferencing strength of the relationship between the upper parent node (input variable) and the lowest child node (output variable), as is known to have occurred in other BNs (Marcot et al., 2001; Varis and Lahtela, 2002; Ames et al., 2005; Barton et al., 2008).

Other inconsistencies, such as the misrepresentation of orthogonal weirs as being more dangerous than frowning weirs, were caused by the nature of probability elicitation stage. While the identification of the DAG structure and the variable discretisation stages progressed quickly, with workshop participants finding the cause–effect network intuitive and engaging, they struggled with the process of eliciting the probabilities. The canoeists required careful supervision to fill out the probability questionnaires, which took between 2 to 5 h to complete. Participants often dwelt on questions, thought carefully, requested additional explanation, and reported that answering was difficult. Other researchers have also found the probability elicitation stage to be problematic for expert knowledge providers (Henriksen et al., 2007; Landuyt et al., 2013). Our experience points to both the questionnaire length and the abstract nature of its questions as causing problems. To envisage the multiple states of a set of parent nodes described in text is mentally taxing, and when repeated 120 times likely results in respondent fatigue. Ultimately time demands placed on stakeholders during probability elicitation constrains the maximum potential complexity of BNs constructed using expert knowledge.

4.2. Lessons

We draw a number of lessons from the experience of building the canoeing BN. When expert knowledge is used, DAG structure should be kept simple in two respects. Firstly, the number of nodes, node linkages and node states should be restricted to limit the length and complexity of the probability elicitation stage. Even so, interpolation of conditional probabilities from a subset elicited from the experts (see Das (1999)) will be required for all but the simplest of models. Note that the canoeing BN has 16 nodes and one of the experts needed 5 h to answer the 120 probability elicitation questions.

Secondly, the length of chains of variables in the DAG should be limited to reduce the propagation of uncertainty through the model.

This is possible as the variables only need to be connected through a cause effect relationship, the details of which do not need to be incorporated into the model. A downside of restricting chain length is that when intermediate nodes are excluded, model transparency declines and probability elicitation becomes more abstract.

In addition to DAG simplification, probability elicitation methods need to be improved so that they become more intuitive, engaging and efficient. A promising approach is computer-based visualisation, which can avoid the need to present questions in text. For example, Gill et al. (2010) displayed weirs and their river setting in an interactive 3D visualisation software. This communication medium provides a more natural way by which visible weir attributes like height and steepness can be represented simultaneously. The efficiency of the probability elicitation process could also be improved if stakeholder probabilities were fed during elicitation directly into the BN through a digital interface, rather than being collected in a paper questionnaire. This would enable the model probabilities to be compiled in the presence of the stakeholders, and as a result, for the performance of the BN to be instantly assessed and iteratively corrected.

4.3. Remaining questions

There are a number of additional questions regarding the suitability of BNs for modelling cultural ESs that will need future investigation. BNs cannot easily deal with spatial interactions and feedback loops (Holzkämper et al., 2012), which may constrain their utility when dealing with shifting patterns of land-use or temporal change. This was not such an issue in the present study as weirs occur as discrete landscape elements, so we were able to deal with them on an individual basis. However, weirs do interact, and a series of fun weirs along a stretch of river have a total value that is greater than the sum of the values of the constituent weirs, something that we could not address with the canoeing BN.

Another question we raise is whether BNs inhibit creativity and the deliberative development of new solutions to management problems. There is a need for stakeholders to develop innovative solutions in environmental management (Borowski and Hare, 2007), and as discrete management options are predefined in a BN, then scope for users to later explore new management options is restricted. This was not relevant to the canoeing BN as there are only a few weir modification options, but it may be a problem in situations when the flexibility to integrate novel management interventions is required.

Lastly, some fundamental questions remain on the general principle of modelling cultural ESs. While the relationships and variables involved in determining river quality for canoeing were clear to the canoeists, this may not be the case for other cultural services. Indeed, some cultural values (such as perceptions of spiritual or aesthetic value) may resist reduction to a collection of variables, as concepts may be broad and overlapping (e.g. wildness, naturalness and beauty) and stakeholders may be unwilling or unable separate them. In fact, such a wide range of perceptions of certain concepts may exist that they cannot be defined precisely enough to provide the model with any predictive ability. In order to answer these questions, a better understanding is required of how commonly ecosystem-cultural linkages can be represented as probabilistic networks.

5. Conclusion

The elicitation of knowledge from the canoeists revealed that the value of the recreational ecosystem service of canoeing on the River Don is determined by subjective variables (danger, fun) that are linked to physical variables (e.g. weir steepness) through the personal judgement of canoeists. We suggest that such a mix of subjective and physical variables is typical of cultural ESs.

For this reason the process-based or data-driven models often used to model other classes of ES are unsuitable for modelling cultural ESs. However, by creating a BN to model the impact of weir modification on the quality of the River Don for canoeing, we have shown that it is possible to model at least some cultural ESs using this technique. The use of conditional probabilities to describe the relationships between variables enabled the canoeists to successfully express their opinions on how management variables affected subjective concepts.

The output of the BN was broadly consistent with the verbal description of the canoeists. Some discrepancies, however, indicate imperfect capture of knowledge, which occurred due to two reasons. Firstly the influence of some weir modifications at the top of long chains of variables were poorly inferenced due to the high uncertainties at intermediate nodes. Secondly, the probability elicitation stage was demanding in both time and mental effort, as was demonstrated by the difficulty the canoeists had completing this abstract and laborious stage, and the misrepresentation in the BN of some of their opinions. To avoid these problems expert built BNs must have a simple structure with few nodes that are not connected in long chains. New techniques should be developed to increase the intuitiveness and efficiency of probability elicitation, such as the utilisation of 3D visualisation software to communicate visual variables.

Despite the limitations we have shown that BNs can be used to model some cultural ESs, and we expect their capacity to represent stakeholder values and perceptions will only improve as new methods of knowledge capture are developed.

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